AI and Ethics (2022) 2:41–47
https://doi.org/10.1007/s43681-021-00085-w

OPINION PAPER

Can AI systems meet the ethical requirements of professional decision-making in health care?

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Received: 13 August 2021 / Accepted: 19 August 2021 / Published online: 27 August 2021

Abstract
The ethical issues around the growing adoption of AI are many and varied. This article will focus on the growing use of AI in the context of professional decision-making within health care. It has been suggested that if automation and robotics threaten blue collar roles, then AI threatens the jobs of those in white collar or professional roles. This article will seek to consider the question "How well can AI meet the ethical requirements of being a health care professional?" The paper will begin by considering the fundamental technologies of AI and their limitations. It will then outline the fundamental ethical principles of professional codes of conduct which define what it means to be a professional and what professionals need to be able to do. This will be illustrated by the use of two case studies. Finally, it will consider whether AI systems can do this in light of their inherent limitations.

1 The growth of AI in professional decision-making

As the amount of data available to businesses and public organisations increases, the growing demand to derive value from "big data" increases in parallel. Very often, the sheer quantity of data renders it impossible to analyse by human means and AI is used. Worldwide business spending on AI is expected to hit $50 billion this year and $110 billion annually by 2024 [33].

In health care, automated analysis of imaging in health screening offers potential benefits in terms of speed of analysis and accuracy. In April 2018, the US Food and Drug Administration (FDA) granted approval for IDx-DR (DEN180001) to be marketed as the first artificial intelligence (AI)-based diagnostic system that does not require clinician interpretation to detect greater than a mild level of diabetic retinopathy in adults diagnosed with diabetes [21].

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In December 2018, researchers at Massachusetts General Hospital (MGH) and Harvard's SEAS reported a system that was as accurate as trained radiologists at diagnosing intracranial haemorrhages, which lead to strokes [28].

In May 2019, researchers at Google and several academic medical centres reported an AI designed to detect lung cancer that was 94% accurate, beating six radiologists and recording both fewer false positives and false negatives.

2 The ethical challenges of professional decision-making

2.1 The nature of professionalism

Dreyfus and Dreyfus [8, 9] proposed a model of professional expertise that plots an individual's progression through a series of five levels: novice, advanced beginner, competent, proficient, and expert. In the novice stage, a person follows rules that are context-free and feels no responsibility for anything other than following the rules. Competence develops after having considerable experience.

Proficiency is shown in individuals who use intuition in decision-making and develop their own rules to formulate plans. Expertise is characterised by a fluid performance that happens unconsciously, automatically, and no longer depends on explicit knowledge. Thus, the progression is envisaged as a gradual transition from a rigid adherence to taught rules and procedures through to a largely intuitive mode of operation that relies heavily on deep, implicit knowledge but accepts that sometimes at expert level analytical approaches are still likely to be used when an intuitive approach fails initially.

Knowledge may be divided into explicit and implicit knowledge. Explicit can be attained easily from any codified information [19].

By contrast, implicit knowledge is not expressible in some languages. It is considered intuitive—acquired through practical experience—and as such, is subjective and contextual, and cannot be readily made explicit or formalised [35]. This view of implicit knowledge suggests its supremacy over explicit knowledge: 'While tacit knowledge can be possessed by itself, explicit knowledge must rely on being tacitly understood and applied. Hence all knowledge is either tacit or rooted in tacit knowledge' [40].

Although the Dreyfus brothers acknowledge this division of knowledge, they assert that skills are exclusive instances of know-how or implicit knowledge:

> 'you can ride a bicycle because you possess something called "know-how," which are acquired from practice and sometimes painful experience'

They assert that when we perform a skill, we basically execute implicit knowledge without a connection to explicit knowledge. They believe that skills are automatic dispositions that cannot be readily made explicit.

They go further and propose that the net effect of learning is intuition and define it in terms of implicit knowledge: 'when we speak of intuition or know-how, we are referring to the understanding that effortlessly occurs upon seeing similarities with previous experiences. They use intuition and know-how as synonyms'. In practice, they define skills at expert level almost exclusively in terms of implicit knowledge.

This approach has been developed within the health care context by Benner [1, 38] to model the development of nursing skills, and although highly influential has not been without its critics [10, 11, 16, 36, 43].

Some authors such as Gobet and Chassy [14] claim that the model is too simplistic to be helpful and propose alternatives. Storey et al. [41] refine the Benner approach to address some of its perceived limitations, whilst retaining its essential characteristics.

Pena [34] contrasts this with the use of the Dreyfus model within physician education, where he argues that the model is still applied uncritically [34].

Contrary to the debate raised in academic nursing fields, judging by medical publications and recommendations from academic organisations, the current form of Dreyfus' model is being accepted almost without explicit criticism from physicians.

The progression of skills development has been linked to the degree of autonomy within which individuals may safely and ethically operate. Gillies and Howard [13] argue that the level of proficiency determines the degree of autonomy that practitioners may safely be allowed (Table 1).

2.2 Professional codes of conduct

Dawson [6] argues that there are significant reasons for opting for a professional code of practice as a means of producing ethical conduct:

- *the apparent clarity and simplicity of such a view;*
- *a fixed standard which allows the professional to know what she must provide for the client, and the client in turn knows what to expect from the professional;*
- *an independent and pre-determined criterion, which is written down and can be consulted, so that ambiguity and misunderstandings can be minimised; leading to*
- *a reduced possibility of legal action; and*
- *providing greater satisfaction for both parties.*

Table 1 Six levels of the performance model (Table 3 in [13]

Level	Designation	Description
0	Unskilled/not relevant	The individual is unable to perform this skill even under instruction or the skill is not required in this role
1	Novice	The individual has little or no experience in this aspect. Able to perform only under close instruction or guidance
2	Learner	The individual has some experience in this aspect and is able to perform with minimal day-to-day supervision, but still requires regular instruction or guidance as new situations arise
3	Competent	The individual performs in this aspect regularly and is able to work effectively, without supervision, on a day-to-day basis, but may need occasional instruction, guidance or support when confronted with unusual situations
4	Proficient	Skilful in this aspect. The individual has a wealth of experience and functions with only managerial supervision. Is capable of demonstrating this aspect to others
5	Expert	Highly skilful in this aspect with several years' experience. The individual has an intuitive grasp of the aspect and requires no supervision other than clinical governance. Acts as a mentor and innovator in this aspect

> Codes of conduct are based around a set of rules and as Dawson argues "There would seem to be no problem in a codes approach if we are able to identify in each situation what the appropriate rules are" but "a code of practice can never be rich enough to provide guidance in all situations, perhaps because there are so many ethically relevant factors to take into account."

In practice, almost all of the rules found in professional codes of conduct require judgement on behalf of the professional practitioner. Paragraph 4 of the General Medical Council [12] ethical guidance for medical doctors states:

> "You must use your judgement in applying the principles to the various situations you will face as a doctor, whether or not you hold a licence to practise, whatever field of medicine you work in, and whether or not you routinely see patients. You must be prepared to explain and justify your decisions and actions." General Medical Council [12].

One of the key requirements is to only operate within the limits of the practitioner's competence:

> "You must recognise and work within the limits of your competence."

A key component of the Kennedy report [23] arising from the Bristol Royal Infirmary Inquirydeals with the need to assure that clinical professionals only operate within their area of competence. It highlights the need for effective Continuing Professional Development to keep up with improvements in practice and the need for adequate supervision and management to ensure that this is taking place.

*T*his requirement is echoed in other health-care professional codes of conduct:

> "You must keep within your scope of practice by only practising in the areas you have appropriate knowledge, skills and experience for" Health & Care Professions Council [17]

and this is mirrored in other professional codes of conduct beyond the health care professions:

> "Engineering professionals have a duty to acquire and use wisely the understanding, knowledge and skills needed to perform their role. They should always act with care and perform services only in areas in which they are currently competent or under competent supervision." *Royal* Academy of Engineering and the Engineering Council [37]

3 The limitations of AI technologies: a historical perspective

To consider whether AI systems can meet the ethical requirements of professional decision-making, we shall consider the limitations of two AI archetypes.

3.1 Heuristic-based systems

The earliest expert systems deployed in the 1980s such as MYCIN [29] and XCON [42] were the subject of fierce criticism by authors such as Dreyfus [7] who were able to point to many of the limitations of these systems.

One of the key limitations was the characteristic described as "brittleness", the inability to cope with a problem outside of their competence.

As early as 1960, there had been dramatic examples of brittleness in heuristic-based systems:

> In 1960 there was an indication, in the recently-installed early warning system in Greenland, of a massive impending Soviet missile attack. It was an error, of course; it turned out that the system's radar signals had bounced back off the moon.
> How did this happen? It turned out that moonrises hadn't been been thought of by the designers, so they weren't in the system's model [5]

Disaster was averted when the humans in charge applied a degree of common sense.

Their first thought was to contact the US Government in Washington, but an iceberg had cut the telegraph cable and communication was impossible. When they considered the situation, various factors suggested that this might be a false alarm.

For one thing, the whole system was new. In addition, they realised that Kruschev happened to be in New York, and it seemed unlikely that the Soviets would have chosen such a time for an all-out attack. It turned out that the system had been confused by a rising moon and moonrises had not been considered by the designers, so they were not in the system's model.

By 1975, an expert system known as MYCIN surpassed a typical doctor's ability to diagnose mengitis in patients, but could easily produce false results if asked to diagnose beyond its area of expertise.

Kilov [25] asserts that human expertise can be brittle as well as computer systems:

> "*Experts are often unable to transfer their proficiency in one domain to other, even intuitively similar domains. Experts are often unable to flexibly respond to changes within their domains.*"

One of the purposes of professional codes of conducts is to govern the brittleness of human experts operating in a professional context.

These systems may be viewed in terms of Dreyfus and Dreyfus Novice to Expert skills acquisitions hierarchy as novices—the later levels which depend upon implicit knowledge gained from experience are not accessible to systems built purely on representations of explicit knowledge.

The limitations of rule-based expert systems led to alternative technologies based around machine learning.

3.2 Learning systems

The earliest machine learning applications were artificial neural networks. They were designed to model the neural networks of the human brain and learn from examples offering the potential to incorporate implicit knowledge as well as explicit knowledge, although Savain argues that at a fundamental level they are less different from rule-based systems than might appear [39].

> "A deep neural network is actually a rule-based expert system. AI programmers just found a way (gradient descent, fast computers and lots of labelled or pre-categorized data) to create the rules automatically. The rules are in the form, if A then B, where A is a pattern and B a label or symbol representing a category." [4]

One medical example of the use of such systems to assist human clinicians is in the interpretation of mammograms for the detection of breast cancer (Hiba et al. 2018).

They were able to use a computer-aided diagnosis (CAD) system based on deep convolutional neural networks (CNN) that achieved an accuracy rate in excess of 97% when interpreting a database of over 6000 images drawn from three publicly available datasets of mammogram images, the Digital Database of Screening Mammography, the Breast Cancer Digital Repository and the IN breast database. This error rate compares with up to 30% amongst human radiologists [2, 24].

With error rates this low, it may be argued that it would be unethical not to use such a system as a second opinion where it was available.

However, the results of such automated analysis are acknowledged to be highly dependent upon effective optimisation by the authors and studies in other fields have shown their fragility and demonstrated their susceptibility to contamination of images or even deliberate manipulation [18].

Koteluk et al. [26] state the current situation as:

> "Machine learning (ML) enables human doctors to save their time, hospitals to save money, and patients to receive highly personalized and more accurate treatment. However, the progressing implementation of ML in medicine has many technical and ethical limitations. The main technical issue that ML needs to overcome is the number of potential manipulations of input data that can influence the system's decisions. For example, a simple action as adding a few extra pixels or rotating the image can lead to misdiagnosing and cancer misclassification as malignant or benign."

Further, the inability of such systems to communicate what they have learnt, and justify their conclusions, limits their ability to be deployed without human supervision and suggests that they would meet the requirements of a professional code of conduct for an autonomous professional.

In contrast to heuristic-based systems, their potential to handle implicit knowledge enables them to move beyond the novice level of the Novice to Expert level to the Intermediate level, but their inability to check, explain or justify their results precludes their ability to operate at the competent level required by an autonomous professional.

4 Discussion

In considering the use of AI systems in professional decision-making, it is important to differentiate between the use of such system as aids for human professionals and their use as autonomous decision-makers.

As early as 1975, they were able to demonstrate that used in favourable circumstances, they could outperform human doctors. More recently, use in specific limited circumstances such as mammogram interpretation has demonstrated performance up to ten times more accurate than human operators carrying out the same task.

Where such systems can be deployed in such circumstances under human supervision, and acting only as an aid or second opinion it may be argued that a human professional not taking advantage of such technology would be negligent in their duty to provide the best possible care for their patients.

However, there are significant challenges that remain with the use of heuristic-based systems.

- Brittleness, i.e. the production of completely erroneous results when operating outside their own limits.
- The absence of any ability to understand limits of expertise, and consequent inability to stay within their competency limits.
- Their failure to deal with implicit knowledge, a key characteristic of professional expertise.

These mean that they cannot be deployed ethically as autonomous professional decision makers.

Machine learning systems can handle implicit knowledge, but still have crucial limitations:

- They can be fooled by relatively small disturbances in their data.
- They cannot justify or explain conclusions and therefore are no more able to stay within limits of their competence than rule-based systems.

This still limits their role to valuable decision aids for professionals, rather than autonomous decision makers.

5 Case studies

5.1 Case study 1: NHS Telephone Advice Services

The first national telephone advice service within the UK NHS was introduced as a nurse-led service in 1999 and known as NHS Direct. This followed various pilots including one in Wiltshire reported on by Lattimer et al. [27] who used a randomised control trial to test the hypothesis that the use of such services did not increase death or serious adverse events. They claimed that their local study showed that “This model of out of hours primary care is safe and effective.”

O'Cathain et al. [32] reported on the early years of NHS Direct and found variations in outcomes based on standard vignettes submitted to NHS Direct. At that time, a number of different systems were in use:

> “TAS is an interpretative software allowing nurses to decide from available options the triage outcome they will recommend to the caller. Both Access and Centramax are more prescriptive and indicate the triage outcome for the nurse.”

Additional variations were attributed to the ability of nurses to override the systems as in real life. In practice, the autonomy for nurses to override the system was matter of some debate internally. However, if the nurses were not able to override them, the callers who were sold the service as “nurse led” were being misled and the IT systems were changing role from decision support to autonomous decision makers.

Nowadays, the NHS national telephone advice service is known as NHS 111, and deploys a mixture of registered health-care professionals and unregistered staff. Initial calls are handled by unregistered staff. If they in consultation with the clinical decision support system (CDSS) deem that a clinical consultation is necessary, they will be referred on to a registered clinician. The Integrated Urgent Care Service Specification [30] reported that 70–80% of patients are advised to have contact with a clinician in one setting or another (February 2017 snapshot show ambulance 11.4%, A&E 8%, speak-to GP 10.2%, contact GP 36.6%, dental/pharmacy 4.9% and other services 3.5%). The remainder required simple information which could be handled in the initial call. In 2017, the clinical consultations took place outside of the service leading to a fragmented service and potentially critical decisions made without clinical supervision. The aim since then has been to improve clinical supervision and bring it nearer to the initial response.

Although front-line unregistered staff using the CDSS are not making clinical decisions about care, they are effectively making decisions about excluding people from care or delaying access to care, both of which have clinical consequences. The health advisor role is required to:

- Receive requests for assistance, treatment or care to the NHS 111 call centre.
- Interact with individuals using telecommunications
- Communicate effectively in a health-care environment with colleagues as well as callers to the NHS 111 service.
- Direct requests for assistance, care or treatment using protocols or guidelines by signposting patients/callers to the most appropriate care/service using the Directory of Services where appropriate, guided by CDSS.
- Support the safeguarding of individuals following local protocols and standards. Relate to others in ways which support rights, inclusion and well-being of individuals, supporting individuals to keep themselves safe NHS England and Health Education England [31]

For these key activities, they are required to act within their professional competence, which means only acting in accordance with guidance provided by the CDSS. This creates a situation where at the first point of contact of the patient with the system the CDSS is effectively operating as an autonomous decision maker in either excluding or delaying patients’ access to care.

In terms of the Novice to Expert scale, this requires proficiency at Level 3-Professional and we argue that we have shown that the CDSS can only operate at level 2 Intermediate giving rise to ethical and safety concerns.

5.2 Case study 2: The Ethics of Virtual Assistants by Peter Smith, as a disabled person

The use of virtual assistants is becoming more and more prevalent by the public in general, and particularly by disabled people. As a disabled individual, I rely on a virtual personal assistant to give me advice in a number of ways. Many are quite simple and factual and raise no ethical issues at all. For instance, I may ask my assistant "What Is the Time?" This is an innocent and factual question and raises no issues. However, I may ask advice regarding my medication which could raise ethical issues. For example, I have recently been re-diagnosed with Type 2 diabetes and prescribed metformin, which is making me feel quite ill. Rightly or wrongly, I asked my virtual assistant advice as to the side effects of metformin. My system replied, with a response obtained from reference.com. Now, how do I know that this is the best advice? Is the advice sensible or even correct? And is reference.com the most appropriate site to obtain such information from? The adviser is, of course, taking some decisions on my behalf along the way in getting to an answer. Such decisions could lead to incorrect information which might worry me or even lead me to doing something unsuitable, such as stopping my medication. Bickmore et al. [3] warn of the dangers of this and of using virtual assistants for supporting medical decision-making.

On the other hand, Guerreiro et al. [15] present a study which demonstrates how a virtual assistant can benefit and contribute to healthy ageing in adults with Type 2 diabetes. So, there are clearly positive benefits to be gained by the use of a virtual assistant.

Virtual assistants also build up profiles of us, using data collected from our conversations with them. Such data may be used for other purposes, in the same way that social media build up profiles of users and then use them to feed the same users' content in which they may be interested. What are the ethics of this? How do I know which data my virtual assistant is collecting about me, and to what use it is putting this? Does it know I am disabled? And if so, what is it doing with these data? What assumptions is it making about me when I ask it to search for information? Is it using my profile as a disabled person to optimise its search? And if so, is this truly to my benefit? In what other way might it be using these data? All of these questions may or may not lead to worrying conclusions and answers. What AI technologies are being used to make assumptions about me? Is this purely innocent and aimed to support me? Or are there darker, more worrying, intentions at play? How do we know this? So many questions and yet it is not easy to find the answers. Henschke [20] warns of the dangers of the surveillance aspects of modern technologies including social media and virtual assistants.

In conclusion, virtual assistants can be of significant benefit to disabled individuals, such as myself. However, should I be worried about the decisions it may be taken on my behalf when providing me with answers to questions and other information? We need to explore ways of ensuring that virtual assistants take ethical approaches when storing and using our data. Kaul [22] provides some examples of the way forward to ensure that virtual assistants behave in an ethical manner.

6 Conclusions

In spite of the major developments in big data and processing power which we have witnessed over the last few decades, AI systems cannot meet ethical standards of the codes of conduct which govern human professionals.

In terms of the Novice to Expert scale, AI systems cannot perform safely at level 3 on the Novice to Expert scale, which would be a pre-requisite for an autonomous human professional.

AI systems operating at level 1 or 2 can provide effective decision aids for human professionals operating at level 3 or above, in the same way as a human professional may deploy a human assistant under effective supervision. However, the limitation in the transparency of machine learning systems may mean that human professionals may find it difficult to defend decisions based upon the advice of a machine learning system.

Bodies responsible for professional codes of conduct may wish to supplement the advice to human professionals the extent to which they may legitimately rely on the outputs from machine learning programmes.

Looking to the future, developments such as autonomous vehicles depend upon relying directly upon the outputs from automated systems, as do fly-by-wire aeroplanes, and the legal and ethical debates about liability in the events of failures may well inform the development of professional practice in terms of the use of machine learning both under human supervision and as autonomous decision makers, and lead to modifications in professional codes of ethics and conduct.

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